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PDF APPROXIMATION FOR RADAR DATA

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Rome Laboratory
Air Force Materiel Command
Griffiss Air Force Base, New York

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13. ABSTRACT (Maximum 200 words)
The subject of this report is a new method for approximating the underlying probability density function of random data, called the Ozturk Algorithm, and its application to spatial radar clutter data. This algorithm works extremely well with only 100 independent samples. This is an improvement over classical methods which can only determine statistical consistency with a specified distribution and require thousands of independent samples. The efficiency of this algorithm allows the approximation of the probability density function of the spatial clutter data from a much smaller region. This makes it possible to observe changes in clutter statistics over a scan volume. The analysis in this report used the algorithm to approximate how close the data from a clutter measurement experiment was to being Gaussian. This analysis determined that the majority of this spatial clutter data was non-Gaussian.

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TABLE OF CONTENTS: PAGE

1.0 Executive Summary

As radar system design has advanced, it has become more important to detect weak signal targets in a strong signal clutter background. Many researchers develop techniques to combat clutter on the assumption that the clutter statistics are Gaussian in nature. This includes much of the research performed in the space-time adaptive processing (STAP) community.

The purpose of the research contained in this report is to provide some insight as to how often spatial radar clutter statistics can be approximated as Gaussian. In order to accomplish this it is desired to evaluate how the clutter statistics change over an entire scan volume. Thus, it is necessary to divide the volume into range/azimuth sectors for data analysis.

Note that the desired analysis is not a typical clutter characterization where data from range cells of similar terrain features and cover types are analyzed. Since it is desired to observe changes in the clutter statistics over the scan volume, the typical range/azimuth sector can contain more than one cover type and/or terrain feature which can lead to non-Gaussian statistics.

At best the number of uncorrelated spatial clutter samples available from a specific radar environment is limited by the range resolution cell size and azimuth beamwidth of the radar. For one scan, this data set will be on the order of several thousand uncorrelated samples for the total scan volume. Since classical PDF estimation techniques require thousands of samples, another more efficient technique was required to perform the data analysis on a given range/azimuth sector.

A new technique, the Ozturk Algorithm, has recently been developed which satisfies this requirement. However, it has only been applied limitedly to temporal radar data and never to spatial data. Thus a part of the objective of this research is to also gain some insight as to the application of the Ozturk Algorithm on measured radar data.

This research found that, in general, the spatial clutter data was in fact non-Gaussian. Also, where the statistics were approximately Gaussian there was no obvious correlation with terrain cover types or terrain features such as trees, shrubs, mountains or water. Thus it can not easily be predicted a-priori which physical areas will be Gaussian.

The issues raised on the application of the Ozturk Algorithm to measured radar data and the potential effects of non-Gaussian

clutter statistics on STAP algorithm performance need further investigation.

2.0 Overview of the Mountain Top Program

The research contained in this report was performed under the in-house effort associated with the Mountain Top program. The thrust of this program within Rome Lab is to develop tools to provide the space-time adaptive processing (STAP) community with a common framework for developing and evaluating STAP algorithms. This effort includes the development of a software analysis tool, RLSTAP, and the collection of measured radar data.

The RLSTAP analysis tool utilizes a "user-friendly" graphical user interface to allow an algorithm developer to simulate a radar signal processing chain with as little software coding as possible. The signal processing chain has been broken into separate modules for the various functions found within a radar system. These modules are represented by glyphs or icons on the computer screen and can be linked to each other simply by "pointing and clicking" with a mouse. A systematic sequence of modules can then be created to represent a signal processing chain. Since the overall focus of the program is in STAP algorithm development and evaluation, RLSTAP is oriented to and most efficient for STAP signal processing chains.

Under the Rome Lab in-house program associated with the Mountain Top project, a large volume of data is available from Lincoln Lab's Radar Surveillance Technology Experimental Radar (RSTER) including an experiment specifically performed for gathering radar clutter data. The radar site was at North Oscuro Peak at White Sands Missile Range in New Mexico. This site provides a scan volume with a significant number of terrain features including the Rio Grande Valley, desert floor, lava beds and mountainous regions as well as various cover types, including range land, scrub brush and forest.

3.0 Motivation

A great deal of research is currently being conducted in the area of STAP processing for separating target signals from interference in radar data. This method estimates a covariance matrix to characterize the input data and uses this matrix to calculate adaptive antenna element weights. These weights form an antenna pattern which places nulls in the direction of strong interference in both the space and the time domains. This technique generally assumes that the statistics of the data used to form this covariance matrix are Gaussian in nature. Researchers have shown, however, that spatial clutter data taken from a range/azimuth sector is not always Gaussian.

The research in this report concentrates on a quick analysis of the spatial radar clutter data in order to obtain an insight as to how often STAP algorithms can expect to have Gaussian data and how often the data will be non-Gaussian. The next logical step is to analyze the performance of STAP algorithms in regions of non-Gaussian data. A non-Gaussian clutter environment may degrade the performance of space-time adaptive processing algorithms. As a result, other techniques may be required for processing signals from radar systems operating in regions of non-Gaussian clutter. The design of these techniques requires the determination of the clutter characteristics. In order to decide when to apply the appropriate signal processing technique, this determination should ideally be made in 'real time'.

Classical PDF estimation techniques for analyzing random data fail to determine the clutter characteristics in two ways. First, they do not provide a PDF to characterize the data. They merely perform a goodness-of-fit test. In other words, they decide whether or not the data is statistically consistent with a specified PDF. Second, classical techniques require a large number of samples, typically several thousand. Often in radar experiments it is difficult if not impossible to obtain thousands of samples.

The Ozturk Algorithm provides a possible solution to both of these problems. First, in addition to a goodness-of-fit test, it also selects the closest approximate PDF from a variety of PDFs. Second, it can approximate the PDF of a data set using on the order of 100 sample points. These capabilities make the 'real time' determination of clutter characteristics in a radar scenario more realizable.

In this particular case, it is desired to determine how spatial clutter data statistics vary over a 360 degree surveillance volume. In order to achieve this it is necessary to analyze the clutter data for limited range/azimuth sector sizes. The available data from the Mountain Top RSTER radar provides

approximately 275 uncorrelated samples in range, covering approximately 115 nautical miles, for each of 50, 3dB azimuth beamwidths. This comes to a total of 13,750 spatial samples for each 360 degree scan. The data is considered uncorrelated in range for each range resolution cell. Thus, the range/azimuth sector size required for the spatial clutter analysis of one scan using classical techniques would be nearly the total scan volume. However, the Ozturk algorithm reduces the required sector size to less than 1/100 of the total volume. It is also possible to further reduce the required sector size by using frequency to provide additional independent samples from the same range cells.

Note that the clutter characterization dealt with in this report is not typical of classical methods of characterizing clutter. Typically, researchers consider clutter data from range/azimuth cells which have the same average slope projected back to the radar and the same terrain and cover type throughout, even though the cells themselves may be from radically different locations. The clutter data considered in this report comes from contiguous range/azimuth cells forming a sector of spatial clutter data. These sectors will in general contain different slopes, terrain features and cover types. This is representative of the data a STAP algorithm will process for an airborne radar application.

Different terrain features and cover types may produce different clutter statistics. It is expected that the mixing of these statistics for two or more different terrain features and/or cover types will produce non-Gaussian clutter statistics in many of these range/azimuth sectors.

4.0 Overview of the Ozturk Algorithm

This section provides a brief explanation of the Ozturk Algorithm without describing the detailed mathematics of the method. The references provide a more detailed discussion of the statistical mathematics used in the algorithm.

The major requirement of the Ozturk Algorithm is that the sample data be statistically independent. This poses a problem for the radar engineer because radar clutter data is not necessarily independent and, in general, there are no readily available tests for determining the statistical independence of a set of random data. In the application of the algorithm described in this report the data was determined to be uncorrelated in range to best meet this requirement for independence.

4.1 The Goodness-of-fit Test

The algorithm itself consists of two major parts, the goodness-of-fit test and the PDF approximation. The goodness-of-fit test is an empirical algorithm which determines if the sample data is statistically consistent with a given distribution, called the null hypothesis, to within a desired confidence level. Typically, the algorithm tests the sample data against a standard Gaussian distribution. However, the algorithm may test the data against any available PDF. The algorithm provides a graphical output as shown in figure 1.

To produce this figure, the data is standardized (normalized to a mean of zero and a variance of one). Then for a sample size of N the algorithm generates M data sets of size N from the null hypothesis using a Monte-Carlo simulation. Each set of N data points is statistically ordered and then transformed into another data set called a linked vector. The magnitude of each component of the linked vector is solely dependent on the ordered statistic of the null hypothesis. The angle of each component of the linked vector is determined based on a Gaussian distribution. The algorithm then determines the average linked vector for the M data sets and plots this linked vector on a two dimensional graph.

The linked vector for the sample data is similarly determined by first producing the ordered statistic of the data. This ordered statistic is then used to determine the magnitude of each component of the linked vector and the angles of each component of the linked vector remain the same as that for the null hypothesis. This linked vector is then plotted as shown in the figure.

The confidence contours associated with the endpoint of the null hypothesis are determined, by fitting a three dimensional bell shape (bivariate Gaussian) curve to the M linked vector endpoints arising from the Monte-Carlo simulation. The contours of constant density of this distribution are then plotted for various values of the parameter alpha, (e.g., 0.01, 0.05, 0.10), where alpha is the probability that the endpoint falls outside the specified contour given that the data is from the null hypothesis. Then unity minus alpha is known as the confidence level and the corresponding contour is known as the confidence contour.

In this research, the confidence contours were selected based on confidence levels of 0.9, 0.95, and 0.99 . If the endpoint of the sample data fell within the innermost confidence contour, then the data is determined to be statistically consistent with the null hypothesis.

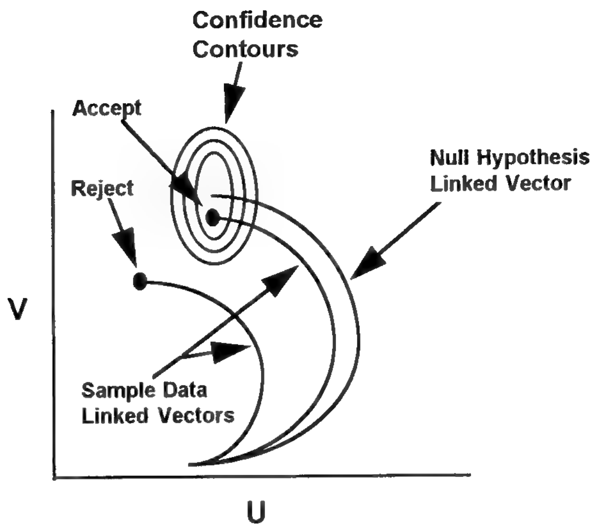
4.2 PDF Approximation

The second part of the Ozturk Algorithm, the PDF approximation, is simply an extension of the goodness-of-fit test. In the PDF approximation, not only does the algorithm plot the endpoint of the linked vector for the null hypothesis, but it plots the endpoints (also based on Monte-Carlo simulations) of the linked vectors for all other available PDFs. Since all data is standardized, distributions dependent only on mean and variance, i.e. with no shape parameters, such as Gaussian, there exists only one linked vector and thus only one point on the approximation chart. For distributions dependent on a single shape parameter, such as Weibull, different values of the shape parameter result in different linked vectors. The endpoints corresponding to the different shape parameter values are joined to form a single curve on the approximation chart. For distributions dependent on two shape parameters, such as the Beta distribution, one curve is generated on the approximation chart by holding one of the parameters constant and varying the other. Then the algorithm chooses a new value for the first parameter and varies the second, generating a new curve on the chart. This process continues until the algorithm generates a family of curves covering the surface that the distribution occupies.

These curves and points comprise the PDF approximation chart shown in figure 1. To select the best approximate PDF, the algorithm plots the endpoint of the linked vector generated from the sample data. It then chooses the closest distribution to the sample data by determining the straight line distance to the curves and points on the chart. The algorithm can also rank order all available distributions based on their respective distances from the sample data linked vector endpoint as well as estimate the shape parameters of any desired PDFs.

It is important to stress here that although the algorithm uses the linear distance from the sample data linked vector as the criterion to order the various distributions, this is not the most accurate method, only the simplest. In general, the confidence contours for the goodness-of-fit test are usually elliptical and nearly circular for data which is on the order of 100 points. However, under some conditions these contours may become quite elongated. Figure 2 demonstrates in an exaggerated manner how the linear distance method can be inaccurate. The sample data point is clearly closer in linear distance to PDF #1 but it is statistically consistent only with PDF #2. Therefore, the linear distance computation can give an idea of the best PDF to approximate the data, but the most accurate method is one which determines the highest confidence level associated with each PDF. The linear distance method was chosen over a method of this type due to its computational requirements and complexity.

It is important to note that the Ozturk Algorithm does not identify the underlying PDF, it approximates the PDF based on a limited sample set size. This has caused some confusion to the authors in the past in that if a set of data is generated from a known PDF, the algorithm will not necessarily rank this PDF as number one. This is due to the fact that 100 samples will not exactly represent the distribution from which it was generated. However, the endpoint of the sample data linked vector will generally fall somewhere within the confidence contours for the distribution from which it was generated if it is statistically consistent with this distribution. Since the data endpoint can fall anywhere within the confidence contours from which it was generated, and typically there will exist more than one PDF within these confidence contours, then it is probable that a PDF other than the actual PDF will be selected. It has been shown, with simulated data, that the approximating PDF is quite good for sample sizes on the order of 50 to 100 points. Typically, the confidence contour for the approximating PDF will overlap that of the actual PDF in the region where the endpoint lies. Providing more points to the algorithm increases its accuracy, however it also decreases the efficiency.



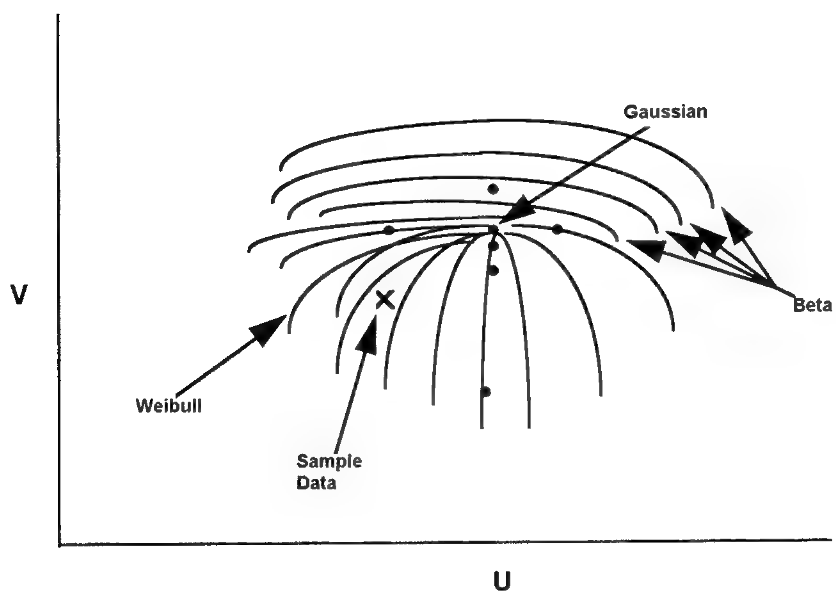


Figure 1: Goodness-of-Fit test (above) PDF approximation chart (below)

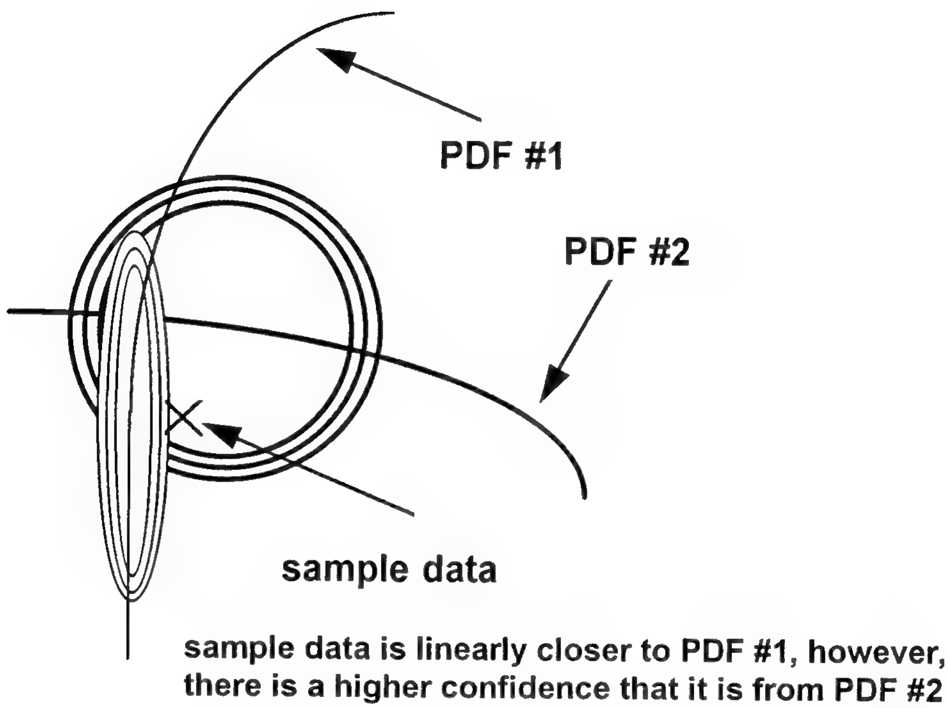


Figure 2: An exaggerated illustration of the inaccuracy in using the linear distance measure to determine the closest approximating PDF

5.0 Selection of Radar Data

Under the Rome Lab in-house program associated with the Mountain Top project, a large volume of data is available from Lincoln Lab's RSTER radar including an experiment specifically performed for gathering radar clutter data. The radar site was at North Oscuro Peak (NOP) at White Sands Missile Range (WSMR) in New Mexico. This site provides a scan volume with a significant number of terrain features including the Rio Grande Valley, desert floor, lava beds and mountainous regions as well as various cover types, including range land, scrub brush and forest.

This transportable UHF radar was located 1400 meters above the desert floor and had an effective maximum range (radar horizon) of over 200 km. For the purpose of clutter characterization, the antenna was scanned at a 5 rpm rate for four different frequencies. Also there was a constant amplitude, 5 microsecond pulse with a 1 kHz PRF, one pulse per CPI, and a 1 MHz sampling rate. In order to take out the dependency on range and cell size (area), the backscatter coefficient for each range/azimuth cell was computed from the raw radar data. Then the magnitude of the in-phase and quadrature components of these backscatter coefficients was calculated to create a vector of real data for the Ozturk Algorithm. Figure 3 shows a range/azimuth plot of the magnitudes of the backscatter coefficients.

The radar data that was analyzed was collected at two different frequencies, 438 MHz and 485 MHz. We are assuming that two clutter samples coming from the same range/azimuth cell at these two different frequencies are independent. The current version of the Ozturk Algorithm requires 100 samples as an input data vector. Thus only 50 range\azimuth cells are now required to obtain the 100 samples for the algorithm.

Although the Ozturk Algorithm requires independent samples, it is impossible to ensure that the measured radar data samples are independent. As mentioned earlier, there are no readily available tests for determining the statistical independence of a set of random data. Thus the best that can be done is to ensure that the data is uncorrelated.

The analog to digital conversion sampling rate of the RSTER radar is 1 MHz. Therefore, the sampled data points are 150 meters apart in range. The pulse width used to take the clutter data was 5 microseconds. This results in a range resolution of 750 meters which indicates that every fifth data point in range should be uncorrelated.

As a check, we calculated the autocovariance function for a

data set consisting of every fifth point in range for a single azimuth. If enough data samples are present the decorrelation 'time' of the data can be determined easily by performing the autocovariance. An example of the autocovariance function in range is provided in figures 4 and 5. The two plots show the autocovariance at an azimuth of 21 degrees (0 degrees is North, clockwise positive) for data with similar magnitudes (range cells 50 to 250) and for data with more widely varying magnitudes (all range cells). These relative magnitudes for the range cells at 21 degrees in azimuth are plotted in figure 6.

From figure 4, note that when the data contains similar magnitudes, the decorrelation does indeed occur around 5 samples. However, from figure 5 we see that when the relative magnitude changes significantly from one region to another, the data takes longer to decorrelate. This magnitude change is likely due two different clutter regions present in range. Since it is desired to have uncorrelated samples, and as small a range/azimuth sector as possible, every fifth point in range is selected and assumed to be uncorrelated. However, it is important to note that when crossing over two distinct clutter regions, the data is likely to have some correlation and thus the Ozturk Algorithm may not perform well.

The recorded clutter data was taken by collecting three different scans with three overlapping range gates (one range gate per scan). For this initial analysis, in order to reduce the complexity of the problem and to ensure that all data used in the analysis is from the same statistical experiment, only one scan was chosen for analysis. The scan chosen was that which contained the closest range gate, since it would provide the largest clutter signals. This data provided 495, 150m range cells per azimuth.

If the data samples are obtained only in range (along one azimuth) then 37.5km of range would be required to obtain 100 samples from 50 range cells and two frequencies. This would also provide only two distinct sectors in range for each azimuth. In order to increase the number of distinct sectors along range and reduce the possibility of crossing over clutter boundaries within a single range/azimuth sector, the azimuth dimension of the radar was considered.

The recorded data contained approximately 200 points in azimuth (200 cpis). This data consisted of angles from 0 to 360 degrees and is shown in figure 7. The autocovariance of this data is shown in figure 8. From the autocovariance function the data is approximately uncorrelated in 4 samples. The beamwidth of the RSTER radar is approximately 6 degrees and each point in azimuth is separated by approximately 1.8 degrees. Thus every fourth sample point, chosen for analysis, is approximately the beamwidth of the radar.

Then the sector size chosen to obtain 100 uncorrelated samples was determined to be 17 points long in range and 3 points across in azimuth. This yielded 51 samples per frequency from a sector of land approximately 13km long and 18 degrees wide.

In the course of performing the analysis it was found that some clutter boundaries are typically very non-Gaussian. If a clutter boundary existed on the edge of a sector, the results of the analysis of that sector would be dominated by the boundary and not truly reflect the entire sector. Since the sectors are relatively large areas, it was desired to try and isolate these boundaries to gain a better perspective of the statistics of the entire scan volume. Thus a sliding window approach was employed. This sliding window analysis in range and azimuth was performed in the following manner.

Consider the first sector in range starting at azimuth index 1. It consists of all points with an azimuth index of 1, 5, or 9 and a range index which is a multiple of 5 from 5 to 85. The sectors overlap each other in range so the next sector consists of all points with the same azimuth indices as the previous sector and a range index which is a multiple of 5 from 25 to 105. This continues until the entire range extent is covered. The next group of sectors covers the region between azimuth indices 9 and 17. The entire circular region surrounding the radar divided into sectors in this manner yields approximately 620 sectors each with 102 independent sample data points for the Ozturk Algorithm to analyze.

At present the Ozturk Algorithm is coded for 100 sample points. It is possible to recode the algorithm to accept an N size data sample, but due to several considerations including time, duplication of effort on the Mountaintop project, and the desire to perform a quick first-cut analysis, it was decided to stay with the 100 point sample size. Also with 100 sample points the Ozturk Algorithm will obtain more accurate results than with the minimum data set sizes which are on the order of 50 points.

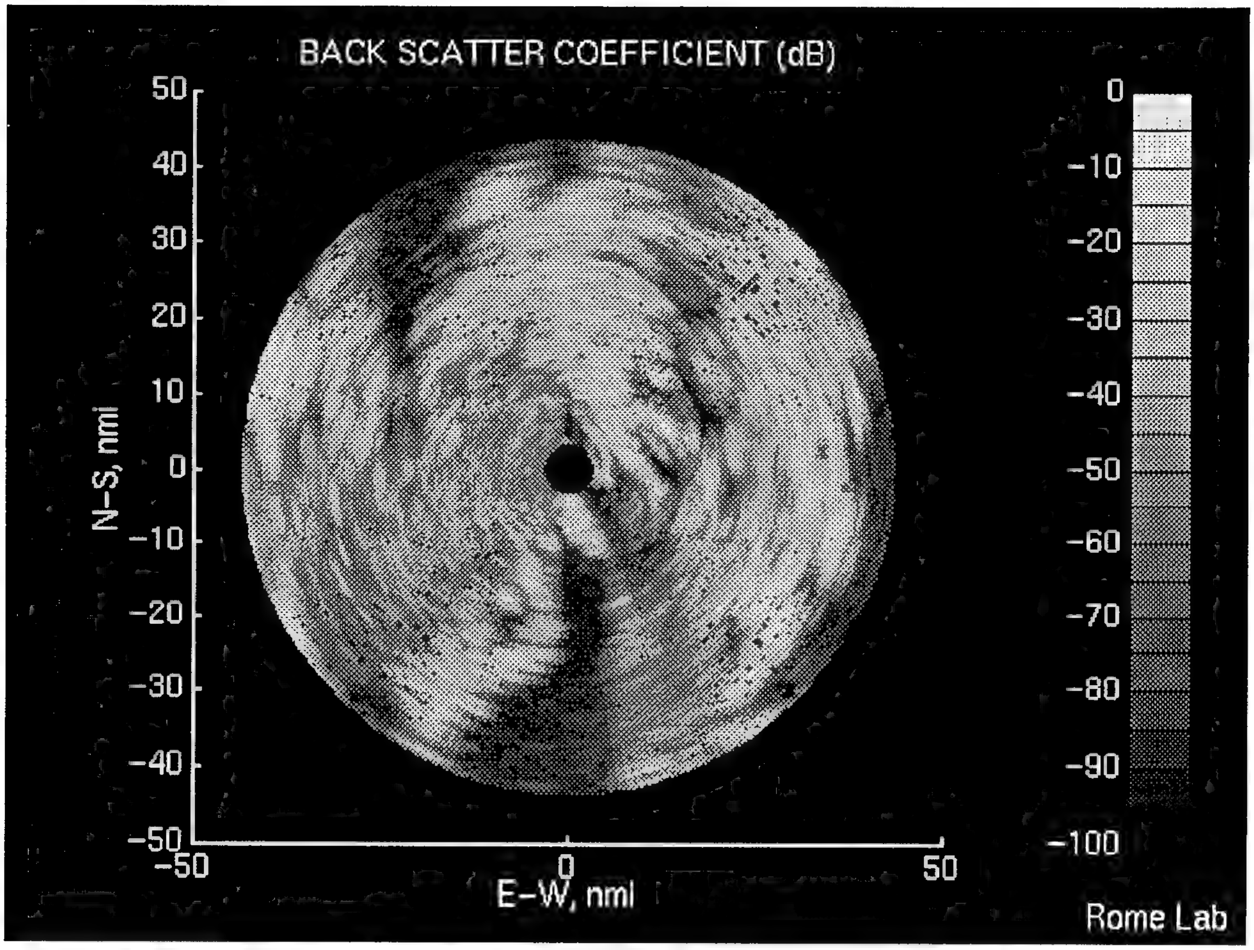
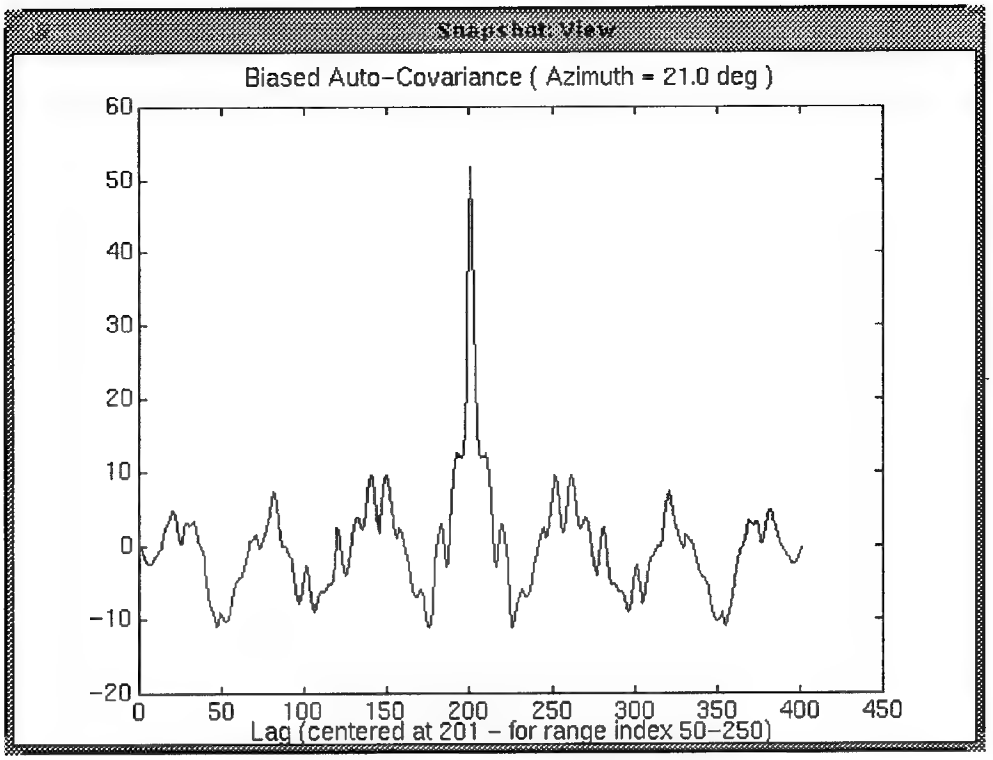
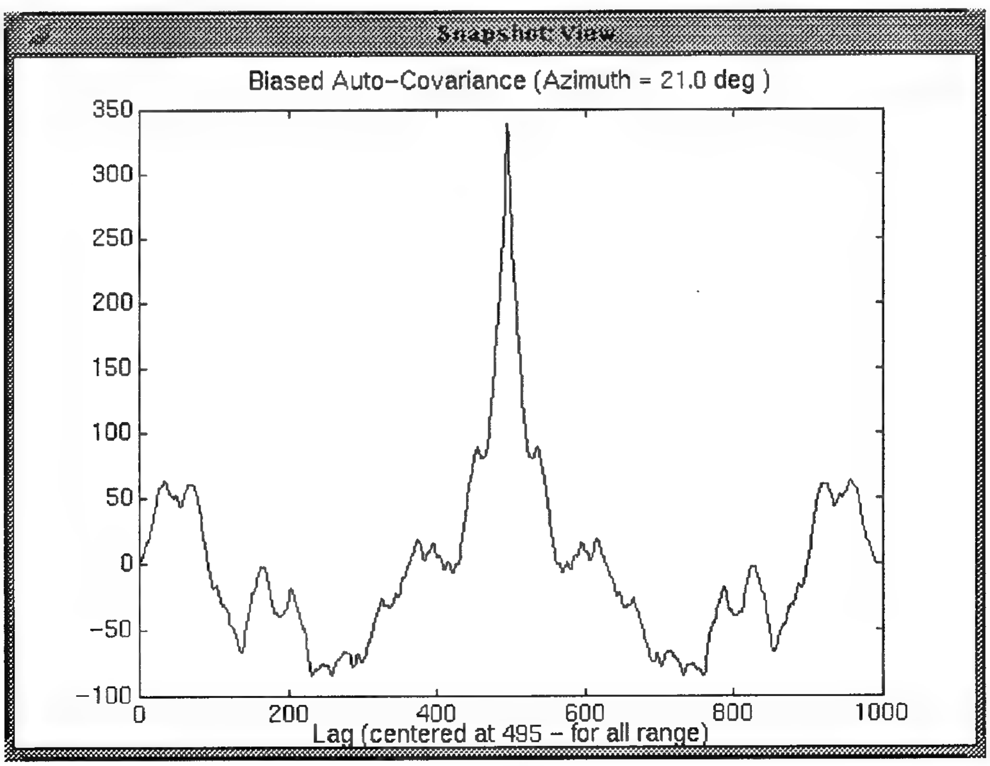


Figure 3: Backscatter coefficient map from RSTER radar for White Sands Missile Range





Figures 4 (top) and 5 (bottom): Autocovariance functions in range for an azimuth of 21 degrees.

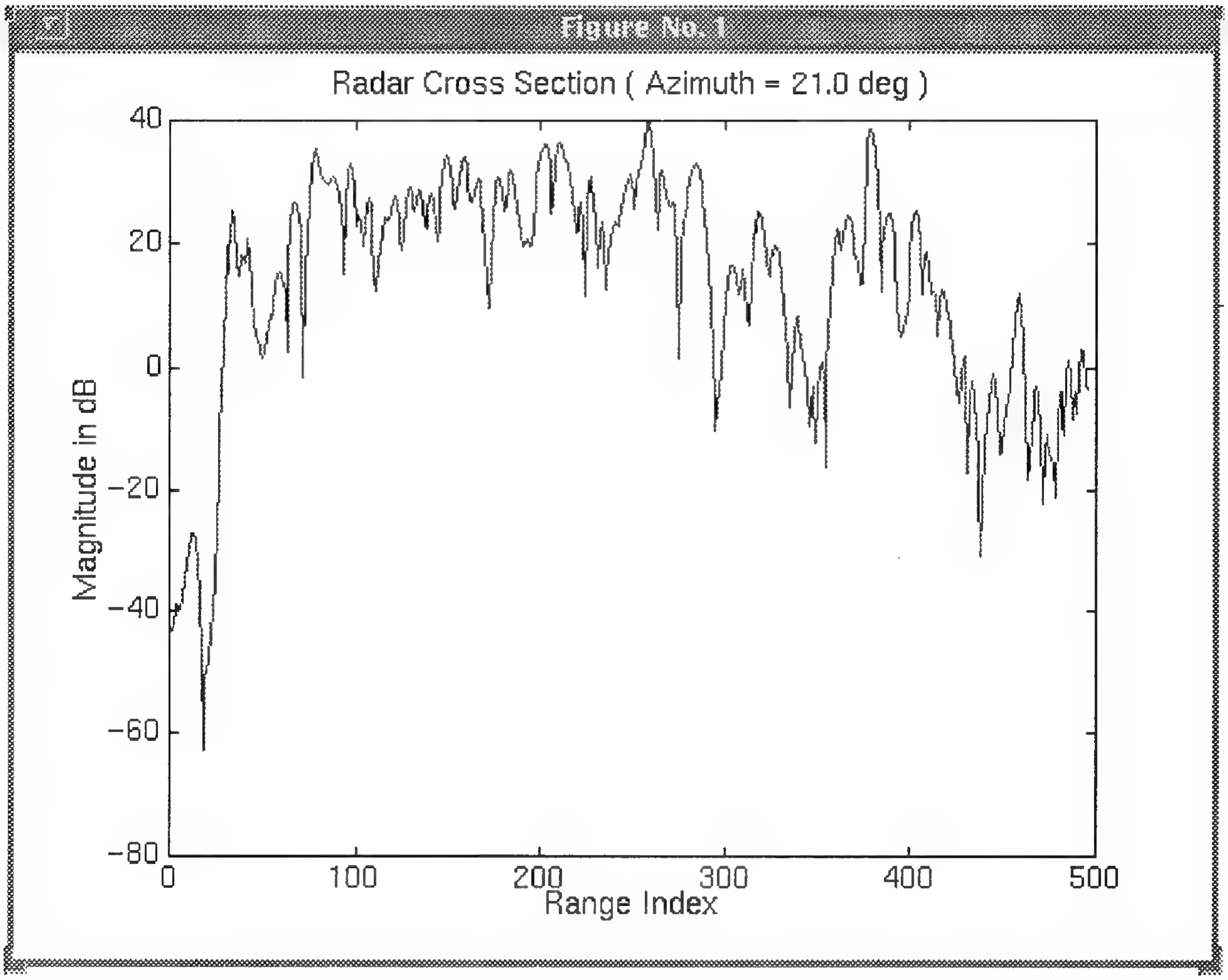
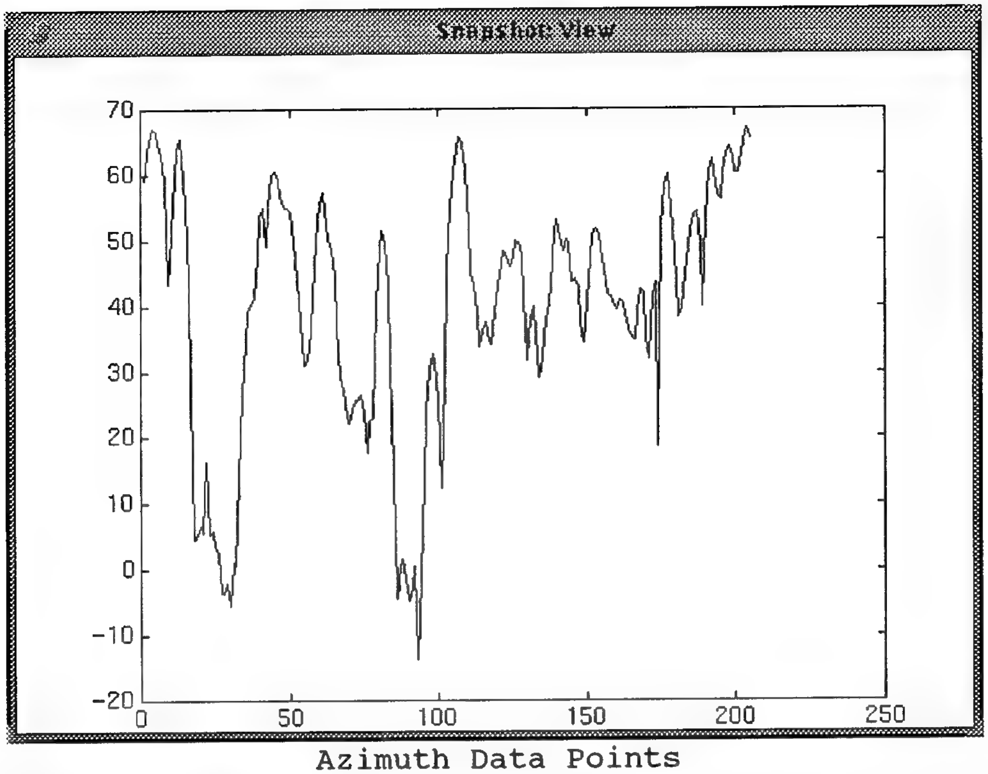


Figure 6: Magnitude data for range cells at 21 degrees



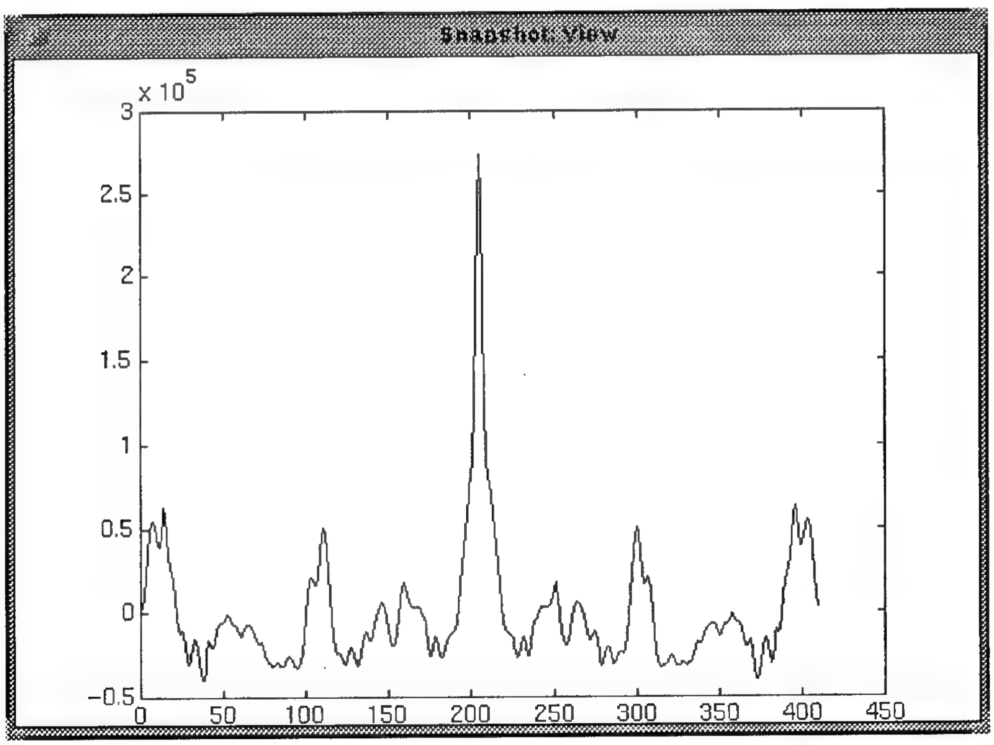


Figure 7 (top): All azimuth data points at 15 km in range.

Figure 8 (bottom): Autocovariance function for data in figure 7.

6.0 Analysis of Radar Data

The primary purpose of the research contained in this report is to provide some insight as to how often spatial radar clutter statistics can be approximated as Gaussian. The typical assumption is that the in-phase and quadrature components are Gaussian with zero mean and equal variance. As stated earlier, in order to obtain real data for the Ozturk Algorithm to process, the magnitude of the in-phase and quadrature components of the radar data was calculated. The statistics of the magnitude data would then be Rayleigh. However, since the Rayleigh PDF is only a point on the approximation chart and cannot itself approximate any other (e.g. non-Gaussian) PDF, the Weibull PDF was chosen for the actual comparison.

The Weibull PDF was chosen to characterize the sample data from each sector since it is commonly used to characterize radar ground clutter data and it has the desirable feature of being identical to the Rayleigh PDF when the shape parameter is equal to 2. The Weibull PDF is,

$$f(x) = abx^{b-1}e^{-ax^2}u(x)$$

Let b = 2,

$$f(x) = 2axe^{-ax^2}u(x)$$

where f(x) is now seen to be the Rayleigh PDF. Therefore, if a Weibull PDF is assumed for each sector, the shape parameter estimate from the Ozturk Algorithm provides insight as to how well the data can be approximated as Gaussian.

It can be shown from a 100 point PDF approximation for the Weibull case, that a shape parameter estimate of less than 1.2 indicates that the associated sample data is definitely not statistically consistent with the Rayleigh PDF. Figure 9 illustrates this in that point X3 which has a shape parameter estimate less than 1.2 is clearly inconsistent with the Rayleigh PDF (endpoint falls outside the confidence contours). However, note in figure 9 that points X1 and X2, both having shape parameter estimates close to 2.0 are not both statistically consistent with the Rayleigh PDF. Thus, to determine if a data sample which has a shape parameter estimate close to 2.0 is statistically consistent with the Rayleigh PDF, the Goodness-of-fit test must still be performed.

The Ozturk Algorithm was then applied to the data generated from each sector from the sliding window analysis. The Weibull shape parameter estimate was then plotted at the center of each sector as shown in figure 10. Some further details of the analysis are provided in tables 1 and 2. Note that figure 10 is not a typical clutter intensity map, rather it simply shows the value of the estimated Weibull shape parameter for the data received from each sector.

TABLE 1: This table illustrates the distribution of the rank order for the Weibull PDF for all 525 range/azimuth sectors

Rank	# sectors < 1.2	# sectors > or = 1.2	Total sectors
1	78	12	90
2	87	16	103
3	89	22	111
4	72	12	84
5	73	6	79
lower than 6	51	7	58
Total sectors	450	75	525

Weibull in top 3 ranks, 304 of 525 sectors => 58%

Weibull in top 5 ranks, 467 of 525 sectors => 89%

Weibull shape parameter estimate > 1.2, 75 of 525 sectors => 14%

Table 2: This table illustrates the number of occurrences a given distribution was identified as the 1st, 2nd and 3rd choice approximate PDF.

Distribution	Number of Occurrences			Total
	ranked 1	ranked 2	ranked 3	
Beta	164	125	89	378
Gamma	97	81	81	259
Weibull	89	105	115	309
Lognormal	53	54	27	134
k-distribution	52	83	92	227
Pareto	33	49	39	121
Gumbel type-2	23	16	37	76
Johnson-SU	14	12	11	37
Exponential	0	0	34	34

Note that Rayleigh is not identified as an approximate PDF, since it is not currently identified as a unique PDF within the Ozturk Algorithm.

Upon close inspection of this plot and table 1, one sees that the Ozturk Algorithm estimates that the Weibull shape parameter for the majority of sectors is less than 1.2. Therefore, this plot indicates that the spatial clutter magnitude data is typically inconsistent with the Gaussian assumption. However, for the areas where the shape parameter estimate is close to 2.0, the data is not necessarily consistent with the Gaussian assumption, as previously discussed.

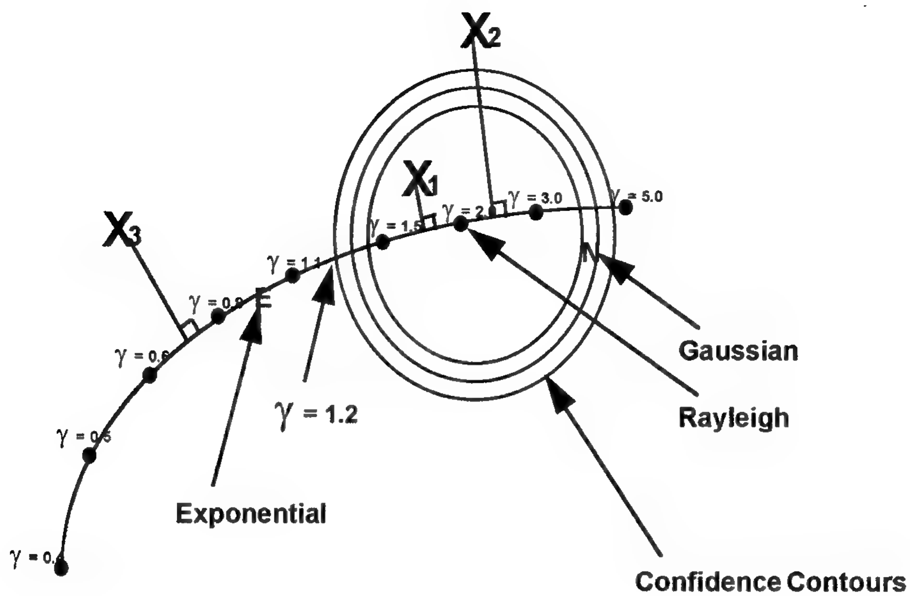
In comparing the terrain height and terrain cover data for the same region (figures 11 and 12) to the plot of the Weibull shape parameter estimates, it can be seen that one cannot predict the value of the Weibull shape parameter estimates based solely on these physical features. For instance, the area to the west of the radar classified as rangeland has a relatively high shape parameter estimate as well as the forested area north of the radar. On the other hand, a second forested region east of the radar has a relatively low shape parameter estimate. Thus there

is no apparent correlation between the shape parameter and the terrain cover. Through a similar comparison, it can also be seen that there is no apparent correlation between the terrain height and shape parameter estimate.

The PDF approximation portion of the Ozturk Algorithm provides further information through a rank ordering of the available PDFs as discussed in section 4.2. Figure 13, shows the sample data endpoints associated with each sector plotted on a portion of the PDF Approximation chart. Only the confidence contours of a Rayleigh PDF and the Weibull PDF curve of the approximation chart are plotted, although many other PDFs are available to the algorithm. This figure indicates, as expected, that the data for which the Weibull PDF was ranked higher are closer to the Weibull PDF curve. In fact for a rank of 1 to 3 the endpoints will generally fall within the confidence contour associated with the estimated Weibull shape parameter. It is interesting to note that for some sectors, the data is not statistically consistent even with the estimated Weibull PDF. In other words, the data can not always be accurately approximated by a Weibull PDF.

In order to provide more insight as to the performance of the Ozturk Algorithm on the spatial clutter data, it is desired to plot the raw data, goodness-of-fit, approximation chart, and histograms for some typical range/azimuth sectors. The first two sectors are typical for a shape parameter estimate close to 2.0 and statistically consistent with the Rayleigh PDF. The associated plots are shown in figures 14-17. The third sector is typical for a shape parameter estimate less than 1.2 but of high rank, figures 18 and 19. The fourth sector is typical for a shape parameter estimate less than 1.2 but of low rank, figures 20 and 21.

The following is apparent from the histograms: 1) in general, the PDF chosen by the algorithm as the best approximate PDF is quite good in all cases, 2) the estimated Weibull PDF is only good for the high rank cases, and 3) the Rayleigh PDF is only good for the first two cases that are statistically consistent with Rayleigh. It is important to note that the histograms are only for 100 sample points. Histograms typically need 1000's of samples to accurately show the underlying PDF of the data. If the bin size of the 100 point histogram was changed, the histogram could appear to be somewhat different. Thus, the 100 point histogram gives an idea of the underlying PDF, but is not an accurate representation. Since there is no guarantee that additional data points from other range/azimuth sectors are from the same underlying PDF, there are only 100 points available for each sector. Thus the 100 point histogram is the best that can be shown for this analysis.



If the Weibull shape parameter for a given sample data set is estimated to be less than 1.2, then the sample data is definitely statistically inconsistent with the Weibull PDF (e.g. point X3)

However, a Weibull shape parameter estimate greater than 1.2 does not guarentee that the data is statistically consistent with the Weibull PDF (e.g. point X2)

The data set is only guarenteed to be statistically consistent with the Weibull PDF if the sample data endpoint falls within the confidence contours (e.g. point X1)

Figure 9: Illustration of the selection of the Weibull shape parameter estimate to determine statistical inconsistence

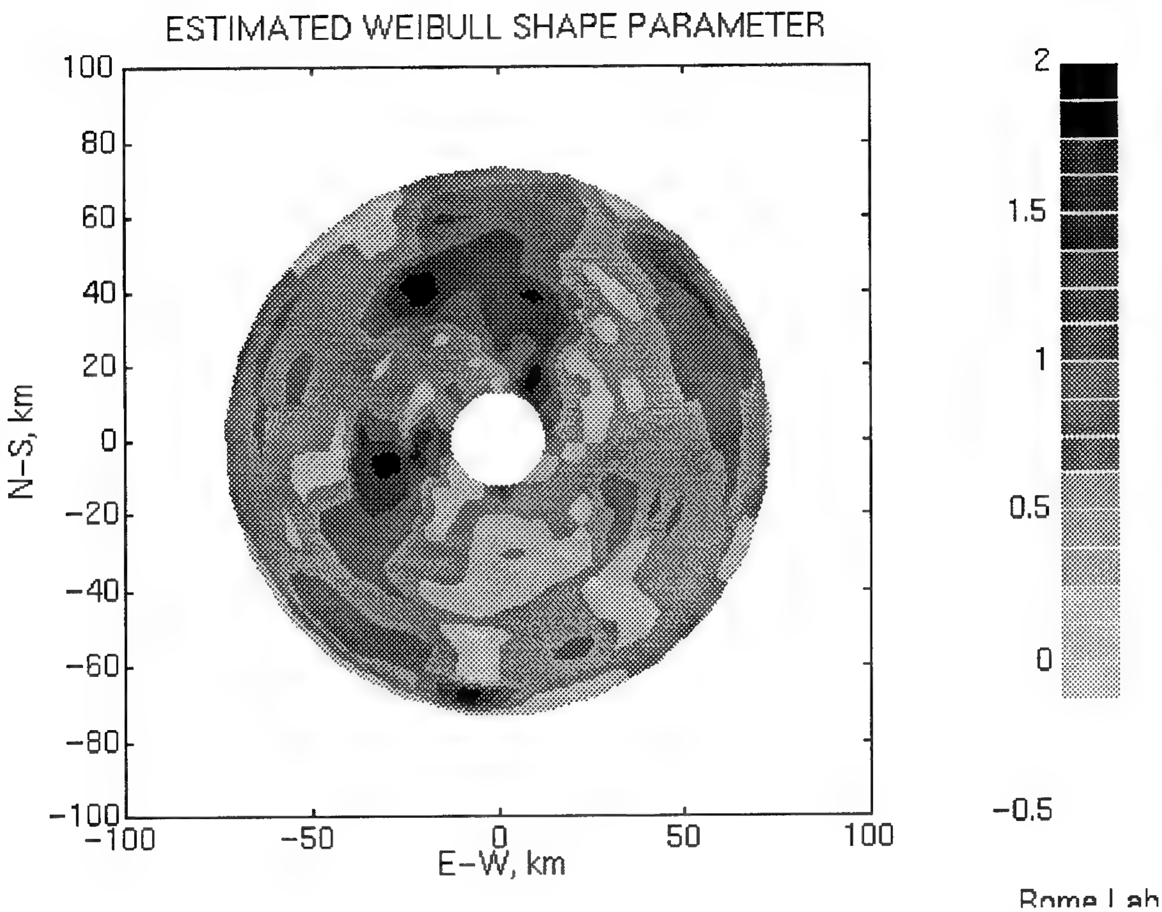


Figure 10: Range/azimuth plot of estimated Weibull shape parameter for all sectors

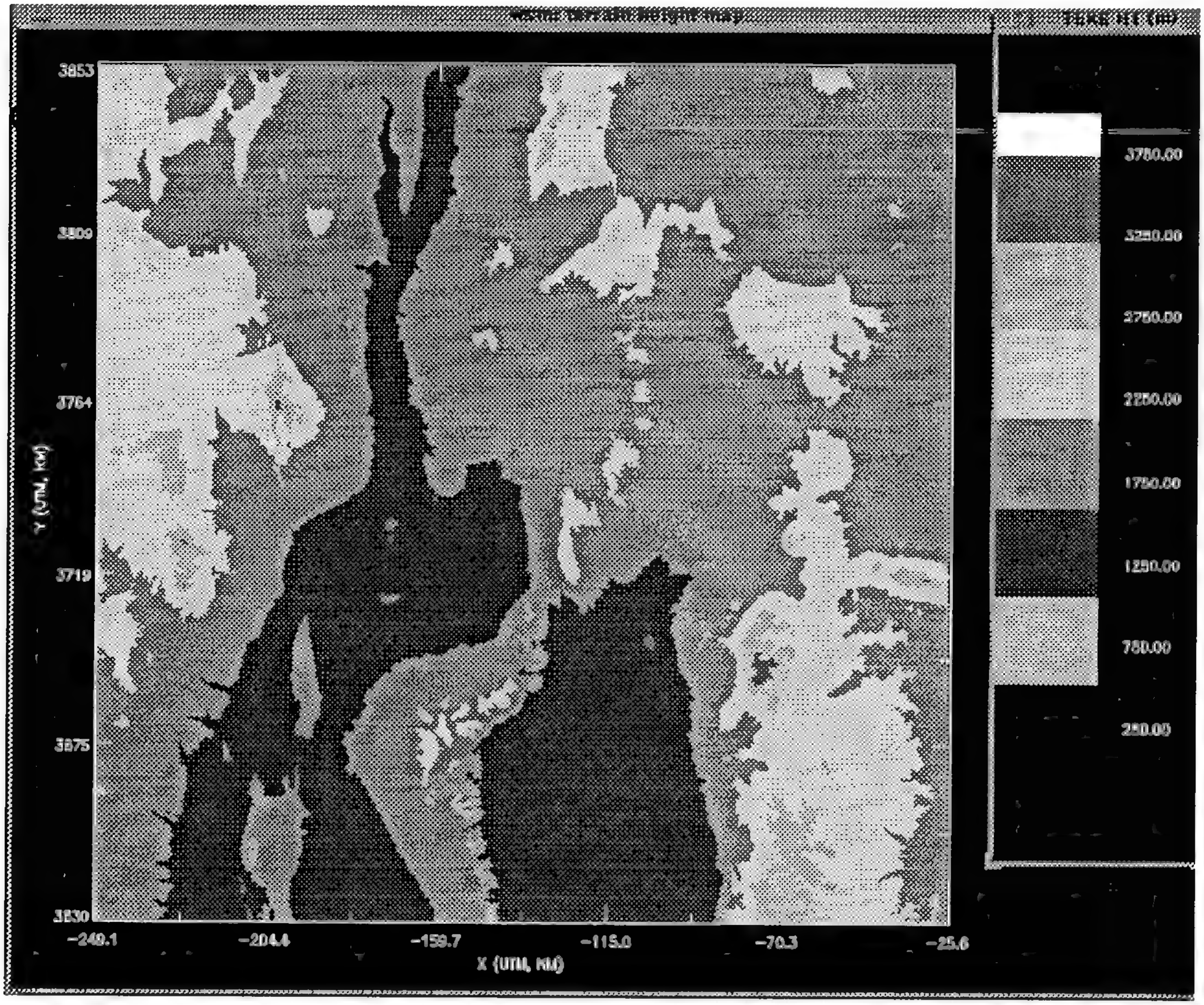


Figure 11: Elevatiom map for terrain surrounding the RSTER radar

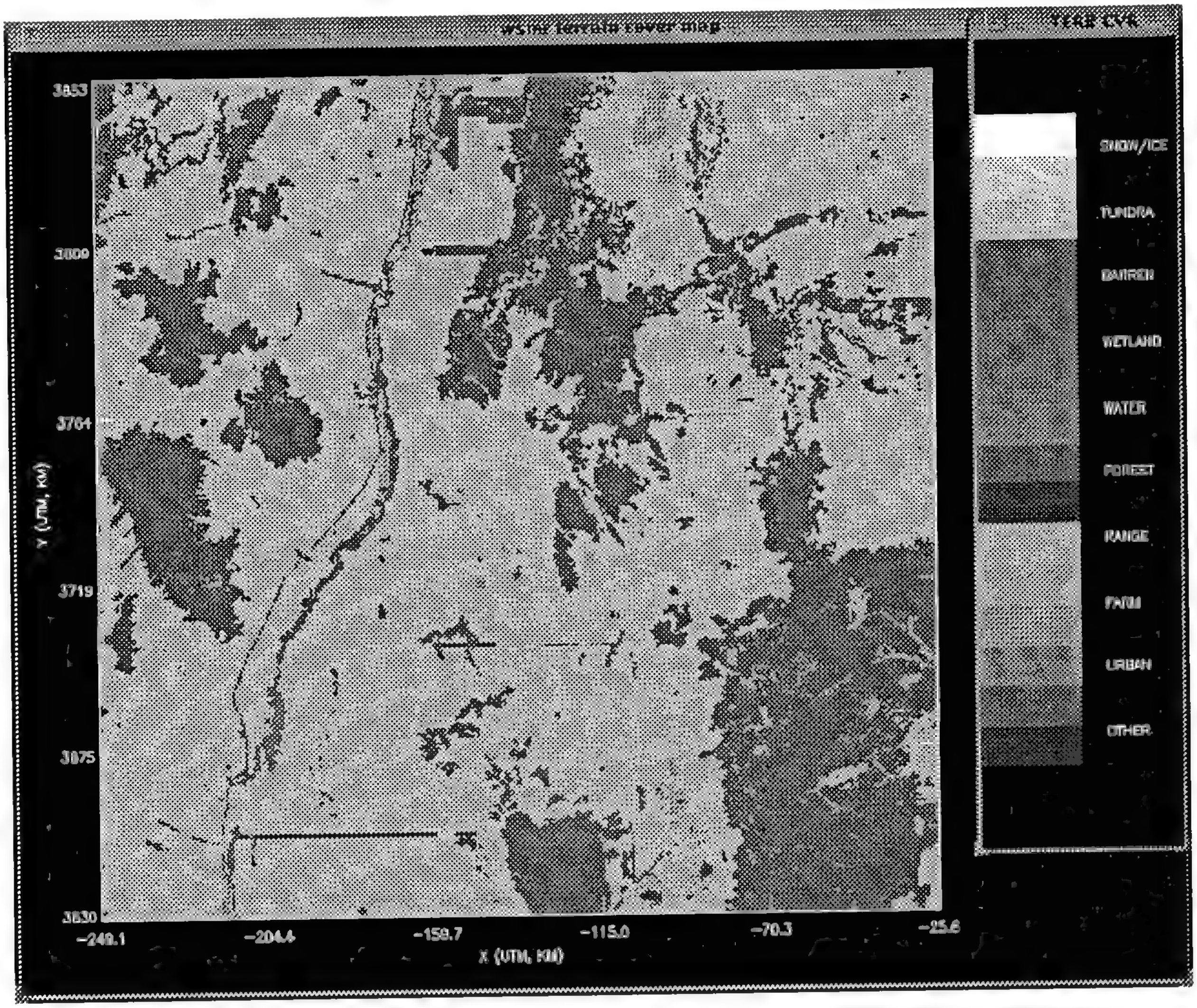


Figure 12: Cover map for terrain surrounding the RSTER radar

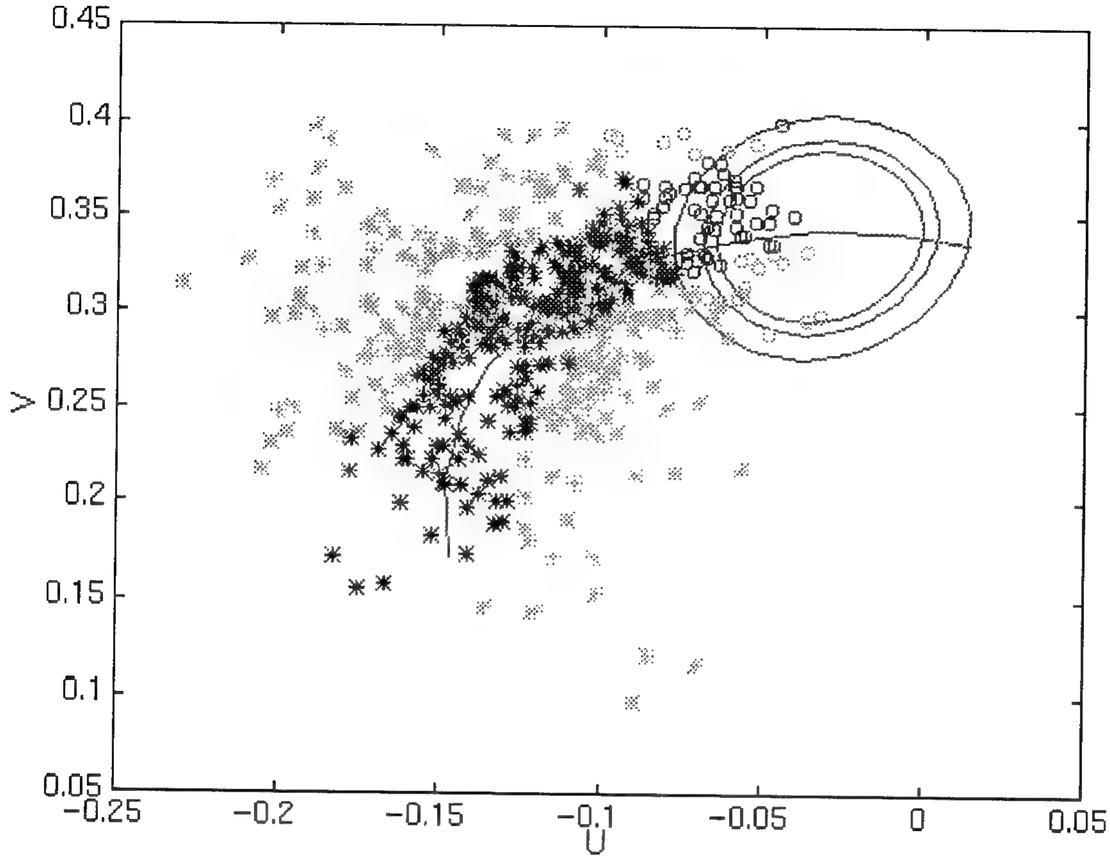


Figure 13: Sample data endpoints for all sectors against Weibull PDF curve and Rayleigh confidence contours

Star - shape parameter less than 1.2
Circle - shape parameter greater than 1.2
Dark - Weibull PDF ranked in top three
Light - Weibull PDF ranked fourth or below

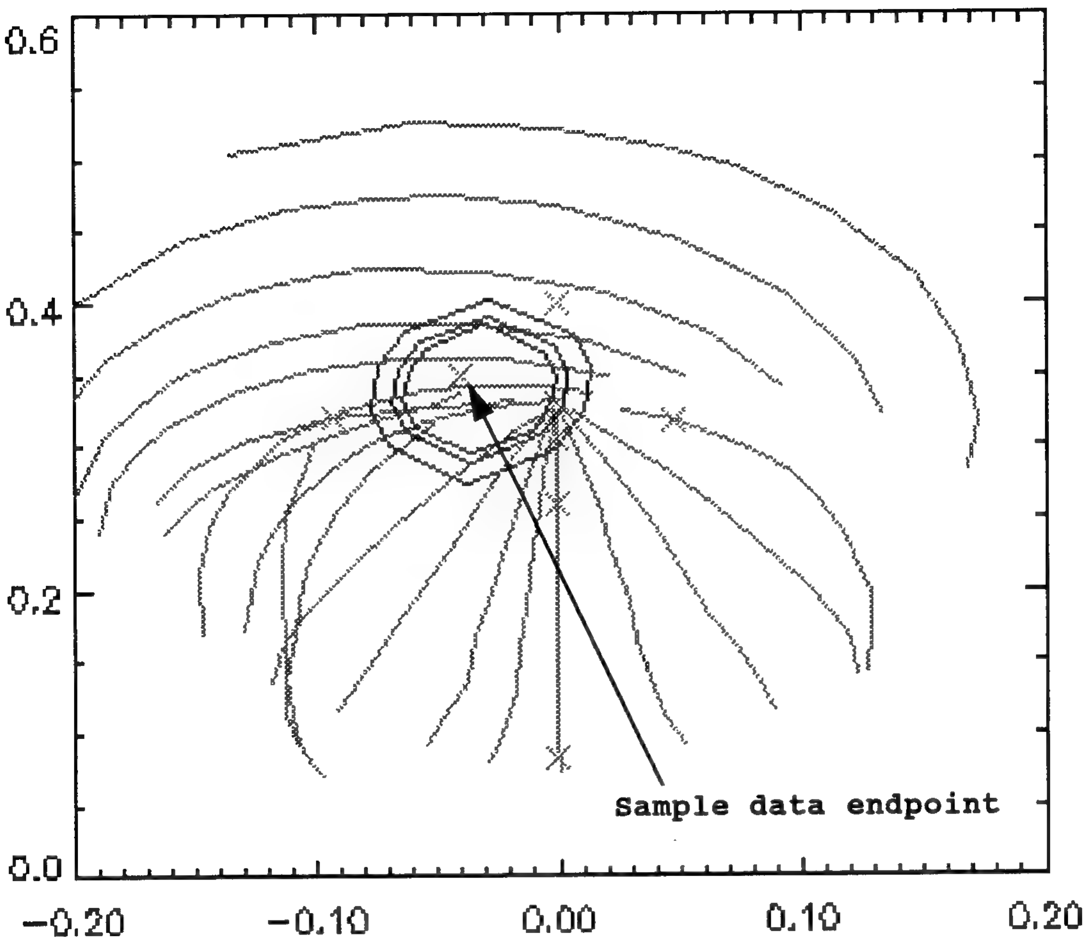
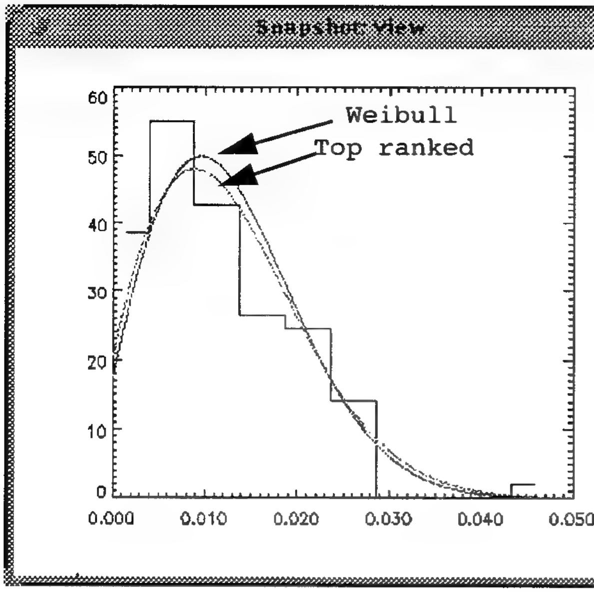
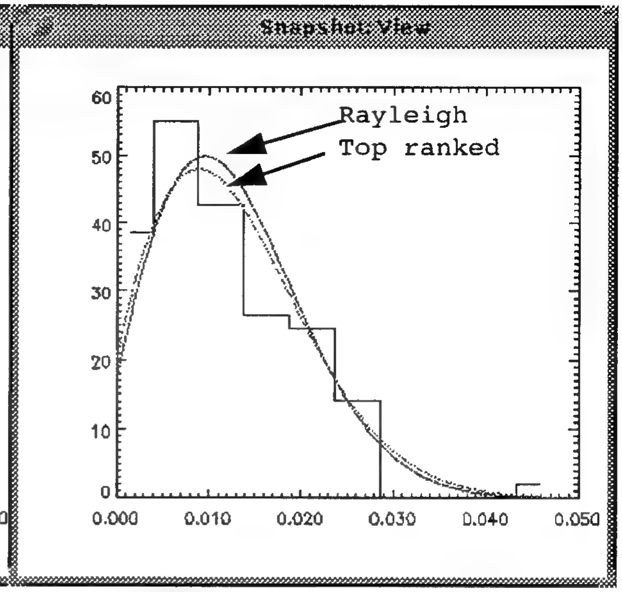


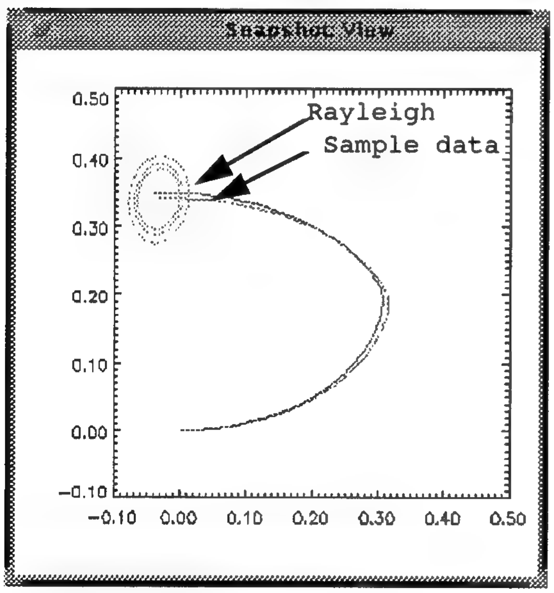
Figure 14 : PDF approximation chart for a sector with a high shape parameter and Weibull ranked highly

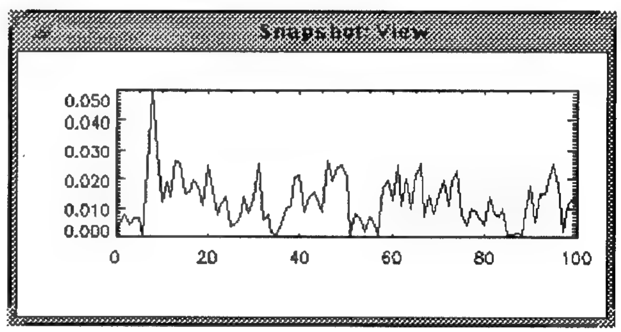




Histogram with top ranked PDF and estimated Weibull PDF

Histogram with top ranked PDF and Rayleigh PDF





Goodness-of-Fit test

Raw data

Figure 15: Plots for a sector with a high shape parameter and the Weibull PDF ranked high

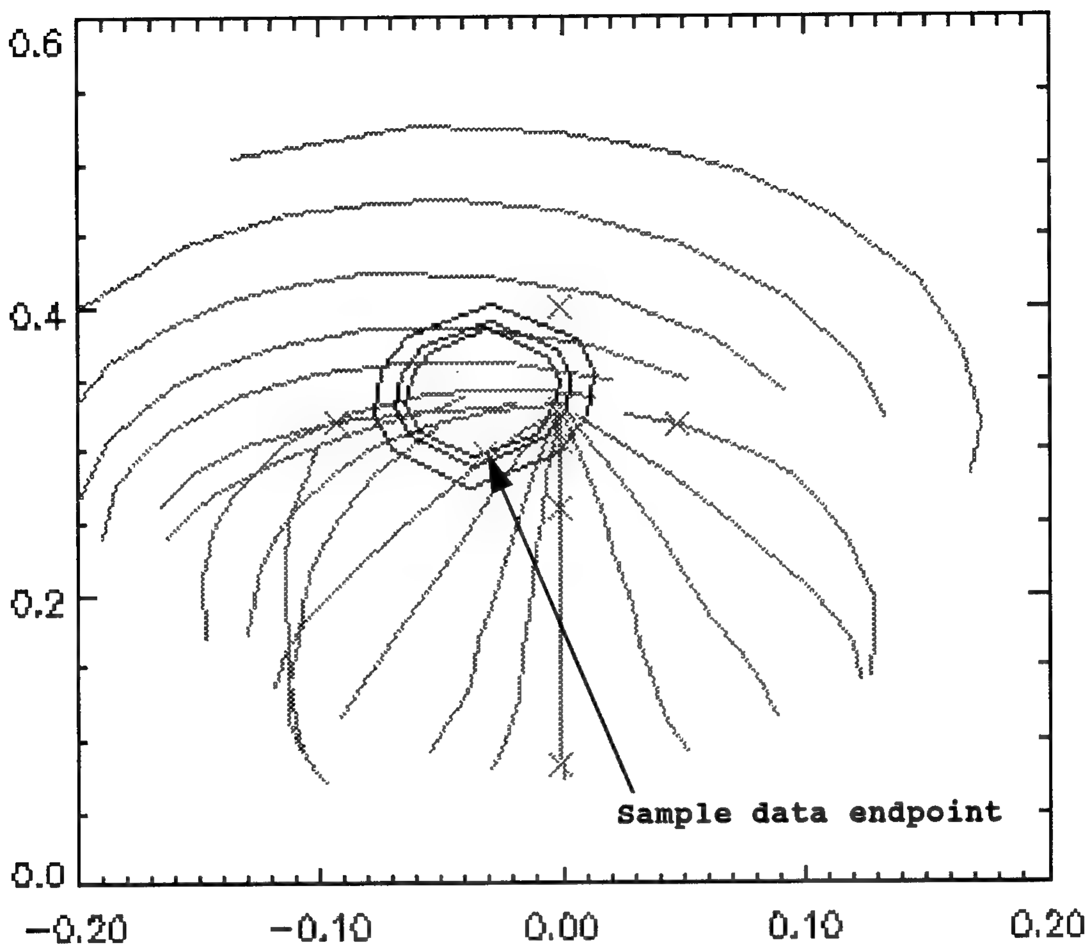
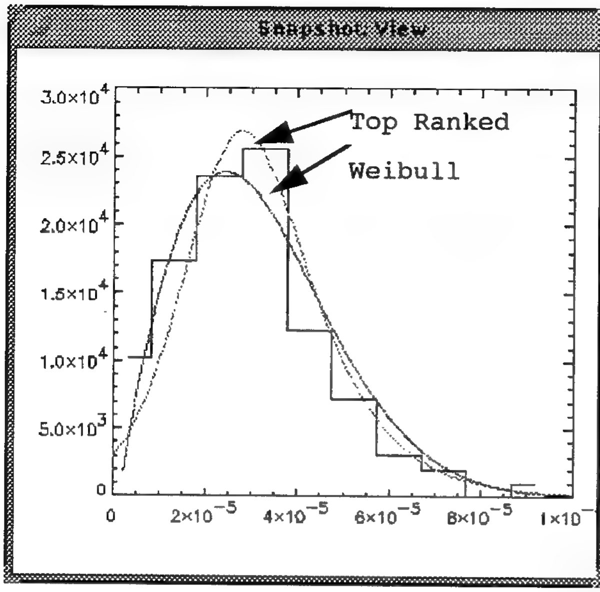
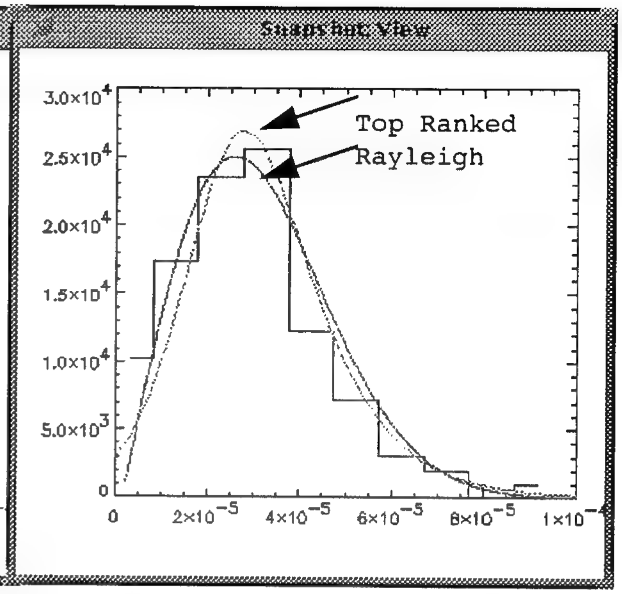


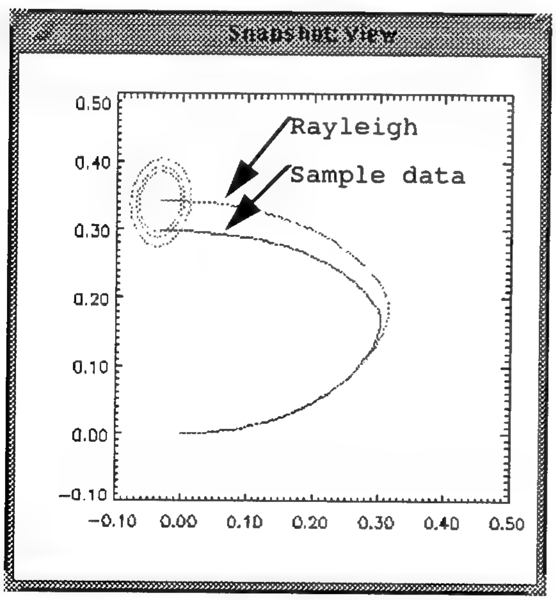
Figure 16: PDF approximation chart for a sector with a high shape parameter and Weibull ranked low



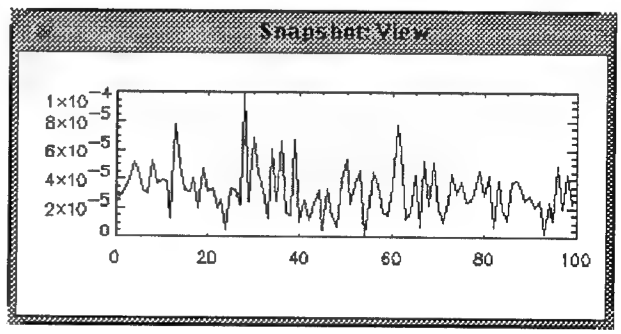
Histogram with top ranked PDF and estimated Weibull PDF



Histogram with top ranked PDF and Rayleigh PDF



Goodness-of-Fit test



Raw data

Figure 17: Plots for a sector with a high shape parameter and the Weibull PDF ranked low

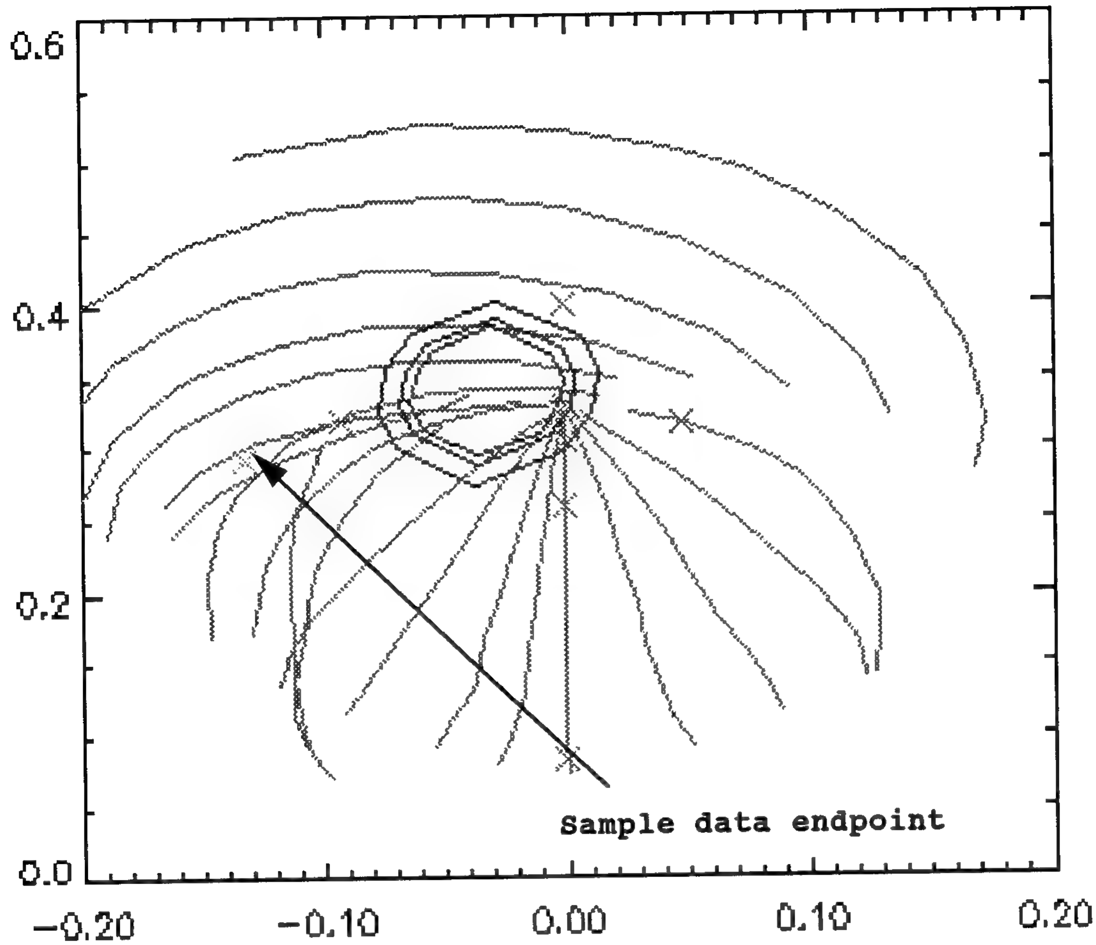
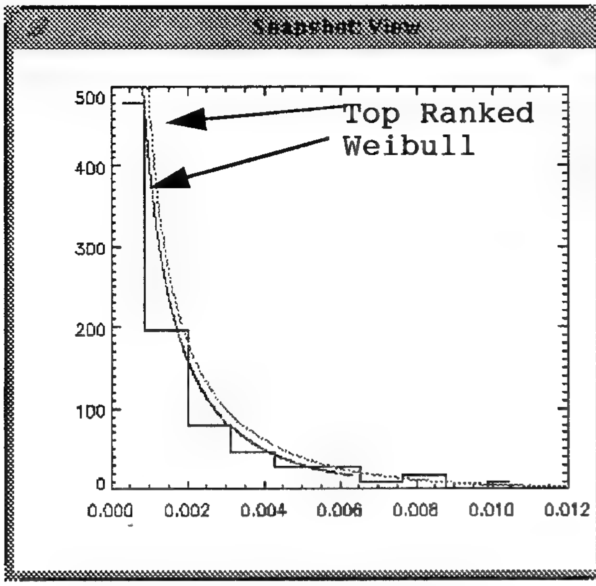
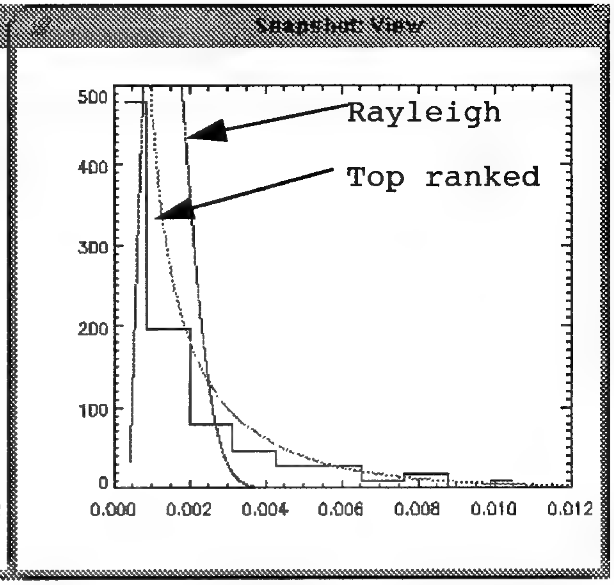


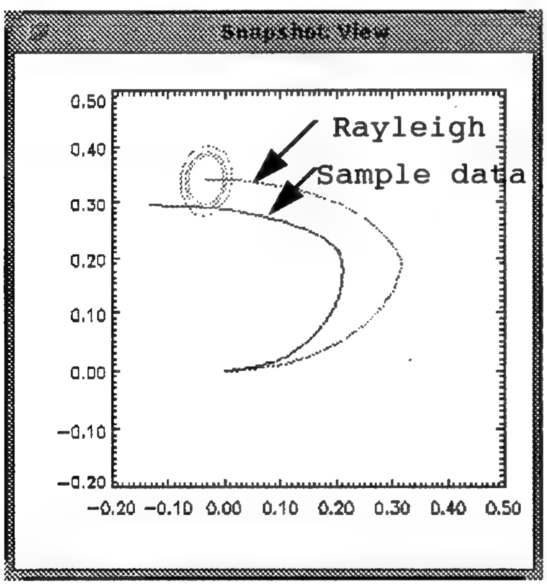
Figure 18: Pdf approximation chart for a sector with a low shape parameter and Weibull ranked high

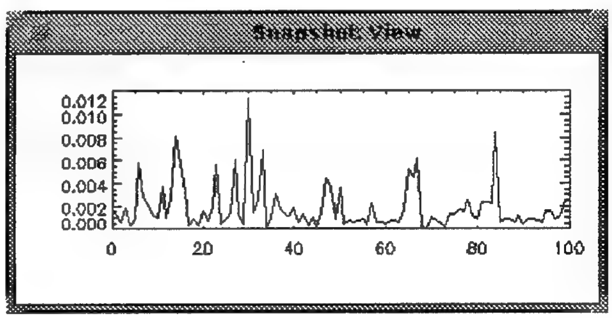




Histogram with top ranked PDF and estimated Weibull PDF

Histogram with top ranked PDF and Rayleigh PDF





Goodness-of-Fit test

Raw data

Figure 19: Plots for a sector with a low shape parameter and the Weibull PDF ranked high

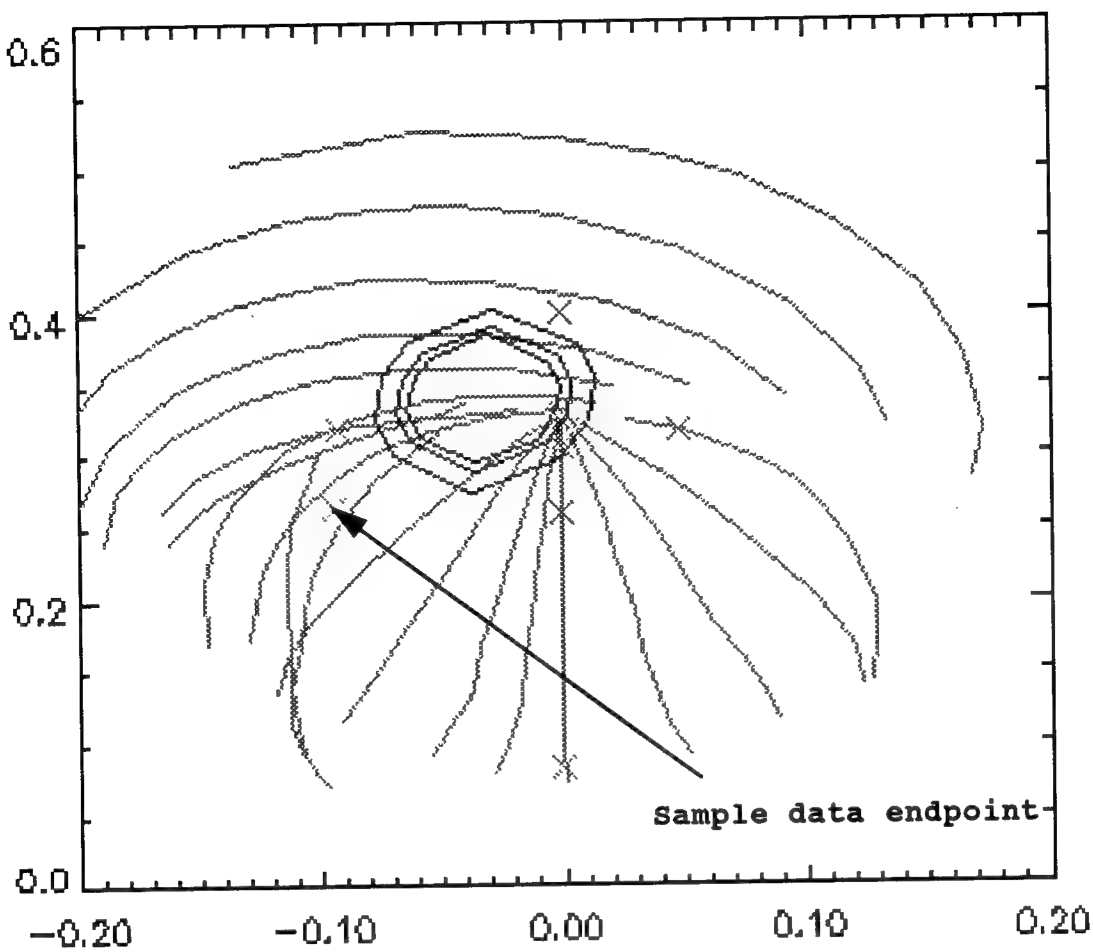
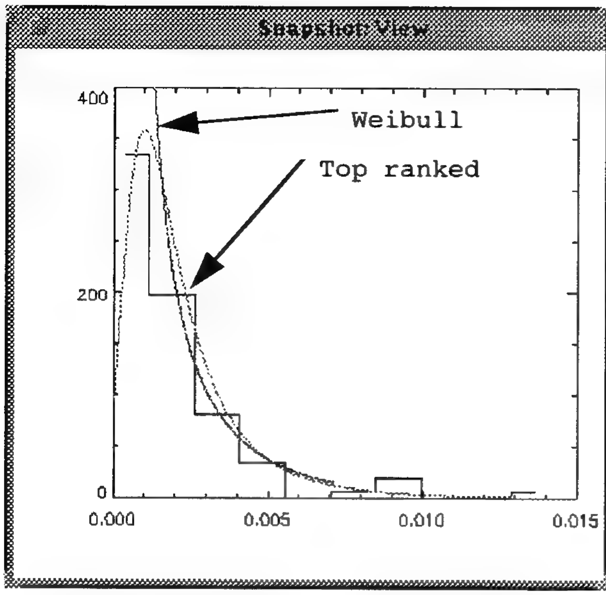
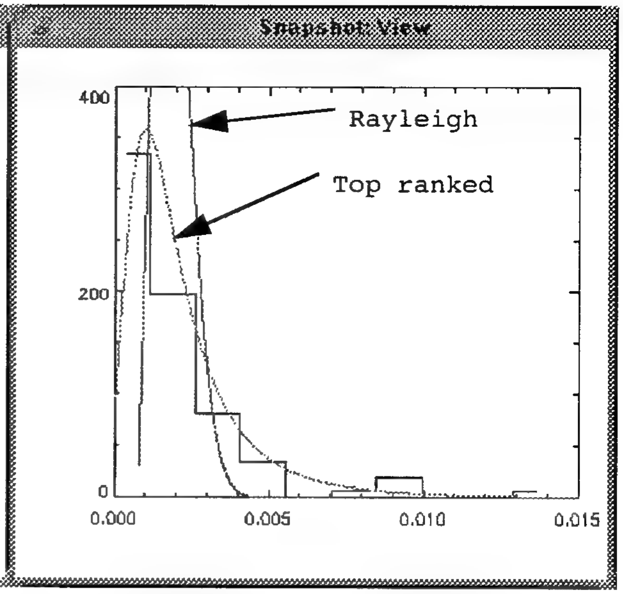


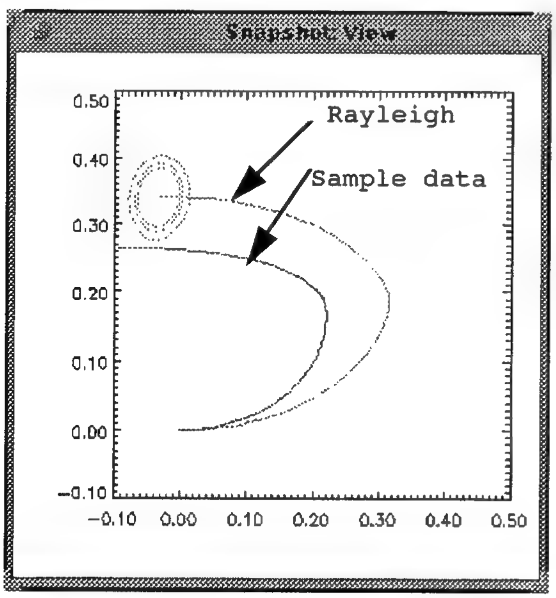
Figure 20: PDF approximation chart for a sector with a low shape parameter and Weibull ranked low



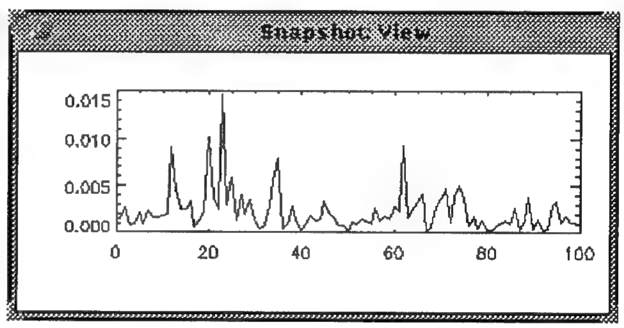
Histogram with top ranked PDF
and estimated Weibull PDF



Histogram with top ranked PDF
and Rayleigh PDF



Goodness-of-Fit test



Raw Data

Figure 21: Plots for a sector with a low shape parameter and the Weibull PDF ranked low

7.0 Application Issues

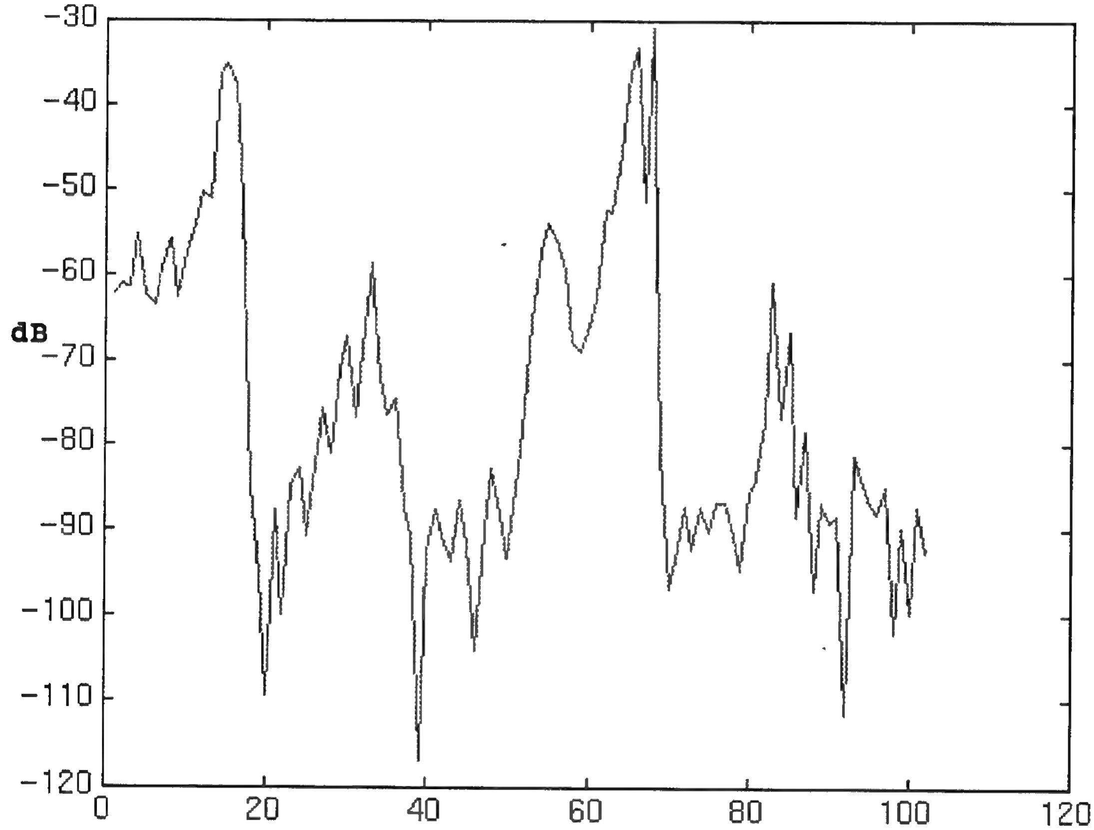
The most difficult requirement of the algorithm for the engineer to deal with is that the sample data must be statistically independent. Radar clutter data is not necessarily independent and there are no tests available to determine independence. The best that can be achieved is to determine that the data is uncorrelated using an autocovariance function or similar technique. Thus, the radar parameters, the number of points used in the algorithm, and the sampling required to obtain uncorrelated data, all determine the minimum range/azimuth sector size for an analysis of the spatial clutter data.

However, after the range/azimuth sector size has been selected, based on some of the data from the entire volume of data, it is not guaranteed that each individual sector used in the analysis will contain uncorrelated data. This was particularly evident in the sectors which contained two or more different clutter regions with significantly different magnitudes. Figure 22 shows the raw data for such a sector and figure 23 shows the autocovariance function, which indicates a decorrelation of the data for every third data point.

At present it is not known how the performance of the algorithm is effected by correlation in the data. From the authors' experience, for small amounts of correlation, the algorithm still appears to perform fairly well. On the other hand, for data where the correlation leads to a bi-modal distribution, the algorithm does not perform well, since it can only approximate the bi-modal distribution with its available unimodal distributions. However, these are only insights gained in the use of the algorithm and not drawn from a methodical performance analysis. It is the opinion of the authors that this analysis needs to be performed to fully understand the application of the Ozturk Algorithm for radar data.

Finally, the current analysis provides a plot of the Weibull shape parameter in a range/angle plot. This indicates when the data is statistically inconsistent from the Rayleigh PDF only for shape parameters below a certain threshold. However, for shape parameters above the threshold, it does not guarantee statistical consistency with the Rayleigh PDF. A better analysis would plot the confidence level associated with data from each sector for the Rayleigh PDF. This would then indicate the amount of confidence that the data from a given sector is statistically consistent with the Rayleigh PDF and would provide a better measure to determine where the spatial clutter data is Gaussian or non-Gaussian. This was not performed in this 'quick look' analysis, since it would require a modification of the current software. However, it should be available in the RLSTAP testbed.

Clutter Data from sector centered at 64 km and 317 deg (2 frequencies)



Vector of Clutter data ordered by range, azimuth and frequency (points 1 to 51 from 438 MHz, points 52 to 102 from 485 MHz)

Figure 22: Radar clutter data (438 and 485 MHz) from a range/azimuth sector which contains correlated data

Autocovariance function from sector centered at 64 km and 317 deg

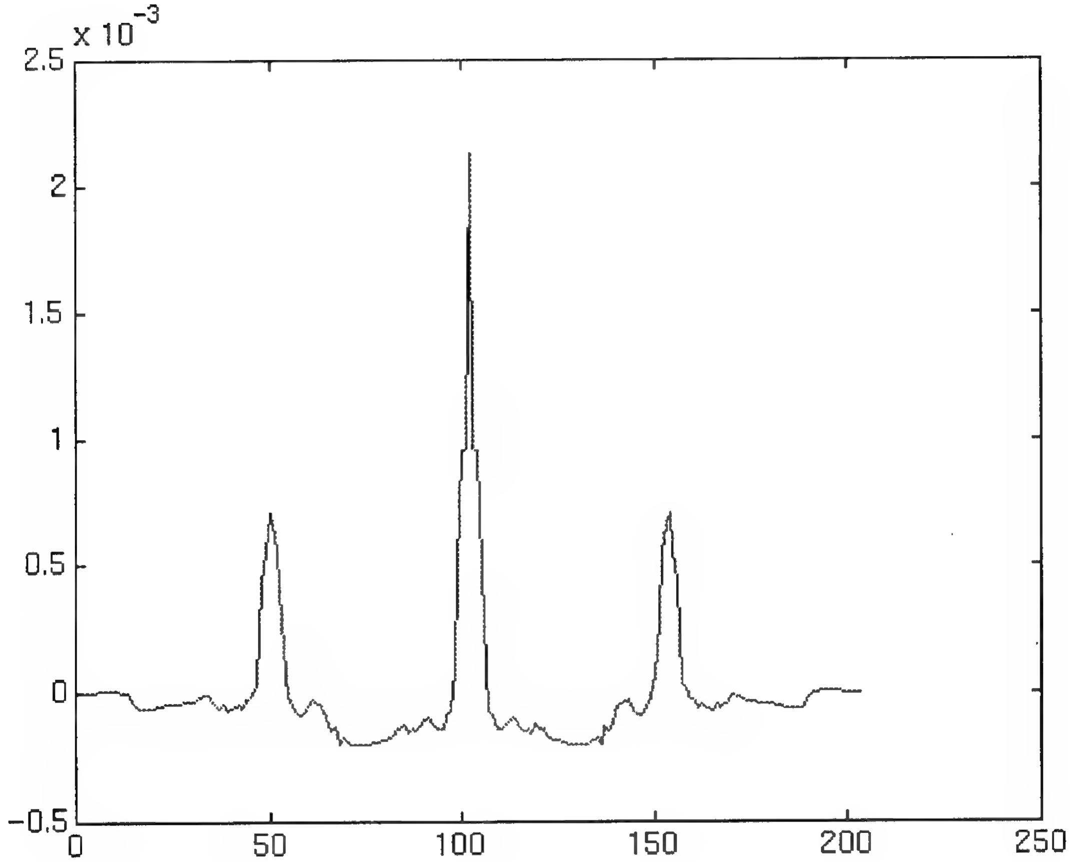


Figure 23: Autocovariance function from a sector which contains correlated data

8.0 Summary

The Ozturk Algorithm seems to be an efficient and effective tool for characterizing radar clutter data. By requiring only on the order of 100 sample points it is possible to perform some analyses which have limited data set sizes and could not be performed using classical techniques that require thousands of points. For the analysis shown in this report, it allowed the range/azimuth sector size to be small enough to provide some insight as to the change of the spatial clutter statistics over a scan volume.

The results of this analysis showed that, in general, it can not be predicted when the spatial clutter data will be non-Gaussian or Gaussian based solely on the physical characteristics of the radar environment. However, the majority of the scan volume was shown to be non-Gaussian. As researchers develop techniques for signal detection in strong non-Gaussian clutter environments, the Ozturk Algorithm will be instrumental in providing statistics of the clutter data using limited data sets. Since, in general, the radar engineer will only be able to obtain limited data sets in the clutter environment for 'real-time' applications, the Ozturk Algorithm will provide a method for determining where non-Gaussian clutter exists. Also, the algorithm provides a best approximate PDF for the non-Gaussian clutter which will enable the application of the appropriate optimal receiver for signal detection.

It is important to note that the analysis shown in this report was based on a 'quick look' of a single radar experiment, thus any implications drawn are not conclusive. It was the purpose of this analysis to gain an insight on how often spatial radar clutter data is inconsistent with the Gaussian PDF and how to best apply the Ozturk Algorithm to radar data. The Ozturk Algorithm requires its input data to be statistically independent and at best the radar engineer can only determine that the data will be uncorrelated. Also, as in this analysis, it may not be efficient to always guarantee that the data is uncorrelated. Thus, future work should concentrate on two issues: 1) the need to investigate the effects of correlated data on the performance of the Ozturk Algorithm to better understand the application of the algorithm to radar data and 2) perform a more thorough analysis of spatial radar clutter data for various radar parameters and environments.

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